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Food Detection and Nutritional Analysis for Customized Dietary Recommendations

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***Abstract*— This diet recommendation system is designed to provide personalized meal plans for individuals with specific health conditions, taking into account user-specific variables such as age, weight, food preferences, and nutritional needs. By integrating an algorithm that estimates nutrient quantities, the system evaluates whether particular food items are suitable for users with specific illnesses. This approach enables tailored recommendations that not only assist users in achieving health goals such as weight management, muscle growth, or disease control but also ensure each suggested food item is appropriate for the user's health condition. Emphasizing fundamental supplements like proteins, fats, carbohydrates, vitamins, and minerals, this system promotes healthy eating habits by suggesting nutrient-dense, well-balanced meals that align with individual goals and dietary restrictions.**

***Index Terms*— Robo flow, YOLO, Nutri scan, Nutrition Estimation, Food Detection, Disease Suitability.**

I. INTRODUCTION

Nutrition is crucial in the management of various health conditions, as appropriate dietary choices can greatly influence health outcomes. Individuals with chronic illnesses such as diabetes, hypertension, and obesity often need tailored dietary plans that cater to their specific medical requirements. However, the development of these personalized diets can be intricate, as it necessitates a careful balance between nutritional needs and the particular limitations imposed by each condition. A Diet Recommendation System aimed at individuals with specific health issues provides a customized approach to meal planning. By evaluating medical information, including the nature and severity of the condition, as well as dietary preferences and restrictions, this system formulates individualized meal plans.

II. LITERATURE SURVEY

We reviewed numerous studies relevant to our project, sourced from reputable journals and conferences, including IEEE, Scopus, and others. These papers provided insights into the technologies and algorithms we need to focus on. Here is a list of some key papers we consulted:
[1] MOHAMMED SHAHEEL: In this diet recommendation system can help individuals achieve their health goals by providing personalized dietary recommendations. They uses less number of highlights which leads to less exactness.

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[2] Saurav Roy, M. Maheswari, Shikhar Jyoti Dutta, and Shreekar Kolanu: This study identifies a number of elements that influence diabetics and assist them in leading healthy lives, which is vital for all people.A quicker method for helping people learn and adopt a healthy lifestyle has been presented in this research.[3]CELESTINE IWENDI, CELESTINE IWENDI, JOSEPH HENRY ANAJEMBA, ALI KASHIF BASHIR, ALI KASHIF BASHIR: this paper proposes a profound learning based arrangement for Helped Understanding Eat less Suggestion Framework Through Machine Learning Demonstrate wellbeing base restorative dataset highlights like age, sexual orientation, weight, calories, master tein, fat, sodium, ber, cholesterol. The study concludes that the LSTM model outperforms other algorithms in accurately classifying food recommendations for patients.[4] HERA SIDDIQUI, AJITA RATTANI , NIKKI K. WOODS , LAILA Remedy , RHONDA K. LEWIS , JANET TWOMEY , BETTY SMITH-CAMPBELL , AND TWYLAJ.Slope:ML models demonstrated effectiveness in obesity prediction, but challenges remain in large-scale real-world deployment. The paper highlights advancements in ML and DL for obesity prediction, discusses current limitations, and suggests future directions for improving model accuracy and reliability.[5] Nanjesh Kumar, Sanjay Kini*, and Sanjeev Badiger: 175 Nitte University students participated in the study, including 93 medical, 49 dental, and 33 nursing nursing understudies of Nitte College with 93 Therapeutic, 49 Dental, 33 nursing understudies . Compared to 46.8% of students who ate out nearly every day, 75% of them experienced stomach troubles on a regular basis.Therefore, we suggest that the urgent need is for a nutritional health education program that aims to improve students' eating habits.[6]Mazher Khan, Hashmi Syed Suhel, Mohammad Zeeshan Raziuddin, Amairullah Lodhi Khan, Syed Wasim Nawaz Razvi, Mohammed Ishtiyaque, Syed Mohsin, R. K. Krishna, Abdul Aleem: A diet recommendation system provides personalized dietary plans based on BMI and preferences, using RMSE to measure predictive accuracy.

Personalized diet recommendation systems have showed a lot of potential thanks to machine learning techniques. The objective of nourishment instruction is to spur people to expend a nutritious count calories. [7] Lee Changhun Soohyeok Lim Kim Chiehyeon and Kim Yeji Jayun Jung Kim Minyoung: They show how the teacher-imposed REINFORCE (TFR) creates a realistic-looking, artificial diet that improves nutrition.Diet planning is first defined in this study as a machine learning problem (i.e., controllable sequence creation), and a successful solution to this problem is developed.[8]Andrew Reynolds, Joanna Mitri: Low GI/GL diets reduce HbA1c, fasting glucose, and cardiometabolic risk factors. Low GI/GL diets show promise in managing diabetes, but further research is needed to confirm long-term benefits.[9] Mahendra Kshirsagar, Prahlad Singh, Rishikesh Pisal, Shreyas Patil, and Arun Ghandat: The recommendation system is regularly improved and refined using this input to keep it responsive and flexible.to user needs over time.

An inventive remedy is provided by the customized diet guidance system described in this research.[10]Reema Golagana, V. Sravani, T. Mohan Reddy,CH Kavitha: This incorporates user's Age,height,weight,blood,sugar level etc. This information is utilized to urge a personalized nourishment suggestion for the specific client. An application can be encourage created utilizing the Quick API system, which permits for the creation of quick and proficient web APIs. [11]Zhidong Shen,Adnam Shezad,Si Chen,Hui Sun,Jin Liu:Machine Leraning Based Approach on Food Recognition and Nutritional Estimation. This study introduces a revolutionary approach that provides information about the kinds of food we consume and its characteristics.After correctly classifying a user-provided image of food, the system provides information about the dish's characteristics.[12] Yudong Zhang Siyuan Lu a a , b , Lijia Deng , Shiting Sun a a , Hengde Zhu , Ziquan Zhu a a , Wei Wang: Deep learning in food category recognition. In this paper they place a particular focus on the most commonly applied approach of transfer learning and the approach that will allow the utilization of potentially abundant unlabeled data: semi-supervised learning. [13] Zhiyong Xiao Jiangnan University Yang Li Jiangnan University Zhaohong Deng Jiangnan University:F ood Image Segmentation based on Deep and Shallow Dual-branch Network. This proposed network aims to facilitate better dietary management by accurately segmenting and recognizing different food ingredients.

III. METHODOLOGY

A. Dataset Description

We extricated this dataset from Roboflow to center on wholesome and dietary data related to different infections. It incorporates 41 passages with each section speaking to a particular infection and related supplement necessities. This dataset contains the taking after columns.Nutritional Measurements:Data on carbohydrate substance, add up to fat, immersed fat, protein, fiber, cholesterol, sodium, sugar, and fundamental minerals and vitamins, counting potassium, magnesium, phosphorus, vitamin C, vitamin A, calcium, press, zinc, vitamin E, and vitamin K, and the dataset's detailed representation follows as:

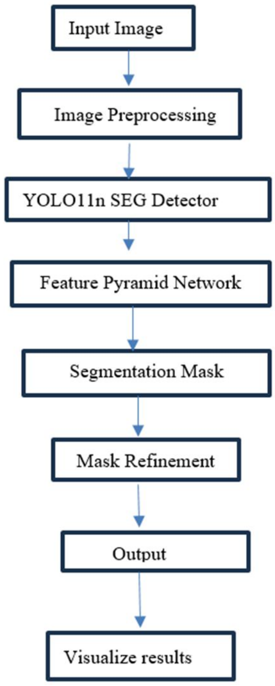
Dataset Structure and Highlights
Infection: This column categorizes each push based on a particular illness . It acts as the essential classification, recommending that distinctive infections may have interesting wholesome needs or limitations.
Macronutrients :- Carbs: The sum of carbohydrates, fundamental for vitality but may ought to be directed in maladies like diabetes. Protein: The protein necessity or constrain related with each malady, which seem change altogether. Fiber: Known to be advantageous for stomach related wellbeing, fiber admissions may be customized per infection. Micronutrients:-Cholesterol and Sodium: Commonly limited in conditions related to cardiovascular wellbeing, these measurements offer assistance screen admissions for disease-specific diets. Sugar: Critical for infections that influence glucose digestion system, such as diabetes. Potassium, Magnesium, Phosphorus: Fundamental minerals included in muscle, nerve work, and bone wellbeing; levels may change based on the disease's affect on organ work. Vitamins: Vitamin C, Vitamin A, Vitamin E, and Vitamin K:These vitamins serve different parts, from safe work to skin wellbeing and blood coagulation. For occasion, Vitamin K may well be observed closely for people on blood-thinning drugs. Calcium, Iron, and Zinc: These are basic for bone thickness, oxygen transport, and safe work, frequently custom fitted in conditions such as osteoporosis or iron deficiency. Image Dataset: we download the pictures from the google to which we need to perform dietary filter to know the amount of each supplement in a specific nourishment thing.

B. Data Preprocessing

This preprocessing decreased the dataset's complexity by expelling a few columns and given clearer naming for less demanding utilize in ensuing investigation steps:
Column Removal: The following columns were dropped from the dataset, as they may have been considered less relevant for the current analysis: Phosphorus, Vitamin C, Vitamin A, Vitamin E, Vitamin K, Magnesium, Calcium, Iron, and Zinc.
Column Renaming: To standardize and clarify the dataset’s feature names, several columns were renamed. The new names make it easier to understand the contents at a glance:Carbs was renamed to Carbohydrates.Protein, Fiber, Cholesterol, Sodium, Sugar, and Potassium were retained but checked for consistency.Disease remained as is.
Data Export: Finally, the cleaned and modified dataset was saved to a new CSV file , allowing further processing and analysis with a simpler, more relevant set of features.

IV. MODEL

A. Model Architecture



B. Parameters Used

Model and Image File
model: YOLO model initialized with "best.pt" to detect objects in images.
results: Detection results of running the YOLO model on "almond.jpg".

Helper Functions and Parameters
get_nutritional_info:
food_name: Name of the food item whose nutrition data is fetched from the API.
calculate_total_nutrition:
food_quantities: A dictionary with food items as keys and quantities as values.
issuitable(total_nutrition, disease:
total_nutrition: Dictionary containing the calculated total nutritional values for the detected food items.

Detected Items
food_names: List of food items detected in the image.
food_quantities: Dictionary storing each detected food item with its user-provided quantity.

Nutrition Information:
total_nutrition: Calculated total nutritional values for detected food items.

C. Model Representation

Here is a workflow flow chart for YOLOv11-SEG model for instance segmentation:

Input
- Image (Height x Width x Channels)

Preprocessing
- Resize image to fixed size (e.g., 640x640)
- Normalize pixel values (e.g., /255)

Backbone
- Conv2D (3x3, 32 filters)
- Conv2D (3x3, 64 filters)
- Max Pooling (2x2)
- CSPDarknet53 (or other backbone network)

Neck
- Spatial Pyramid Pooling (SPP)
- Feature concatenation
- Conv2D (1x1, 256 filters)

Instance Segmentation Head
- Mask Branch:
  - Conv2D (3x3, 128 filters)
  - Upsampling (2x)
  - Conv2D (3x3, 128 filters)
  - Sigmoid activation
- Box Branch:
  - Conv2D (1x1, 255 filters)
  - Decode bounding boxes
  - Non-Maximum Suppression (NMS)

Mask Generation
- Multiply mask predictions with class probabilities
- Apply threshold to gain mask predictions

Output
- Instance segmentation masks (Height x Width x num_instances)
- Detected bounding boxes with class probabilities and scores

Loss Functions

- Mask loss
- Box loss
- Total Loss = Mask Loss + Box Loss

V. RESULTS

By training YOLO on a dataset of various food items, it can quickly identify different foods within an image. YOLO’s single-pass architecture allows for fast and accurate detection, making it ideal for real-time applications like identifying food on a plate or in a photo. Once YOLO detects and labels each food item in the image, it assigns a class name to each detected object, which corresponds to the type of food . This detected class name becomes the input for the next stage retrieving nutritional data. The system integrates the results from YOLO and the nutrition API to display the detected food items alongside their nutritional details. For instance, if YOLO detects "apple" and "sandwich," the system can display calories, vitamins, and other nutrients for each item individually. By linking YOLO's detection capabilities with a nutrition database, this system provides a powerful tool for automated food recognition and nutritional analysis, helping users stay informed about their dietary intake effortlessly.

```
Fetching nutritional information for banana with quantity 1 kg...

Total nutritional values for the selected food items:
Total Carbohydrates: 269.50 g
Total Fat: 3.90 g
Total Saturated Fat: 1.30 g
Total Protein: 12.90 g
Total Fiber: 30.70 g
Total Cholesterol: 0.00 mg
Total Sodium: 11.80 mg
Total Sugar: 144.30 g
Total Potassium: 4224.40 mg
{'Carbohydrates': 247.5, 'Total Fat': 73.0, 'Saturated Fat': 14.66, 'Protein': 60.0, 'Fiber'
: 30.0, 'Cholesterol': 200.0, 'Sodium': 2000.0, 'Sugar': 36.0, 'Potassium': 4500.0}
{'Carbohydrates': 269.5, 'Total Fat': 3.9000000000000004, 'Saturated Fat': 1.3, 'Protein': 1
2.9, 'Fiber': 30.7, 'Cholesterol': 0.0, 'Sodium': 11.799999999999999, 'Sugar': 144.3, 'Potas
sium': 4224.4}
Total Carbohydrates (269.50) is NOT suitable for Thyroid.
```

Fig 1: Displaying Nutritional quantity in 1 kg Banana

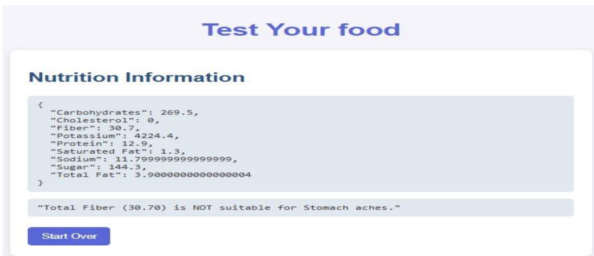


Fig 2: Detecting Banana Nutritional Quantity

Fig 3: Nutritional Information present in Banana After Detecting

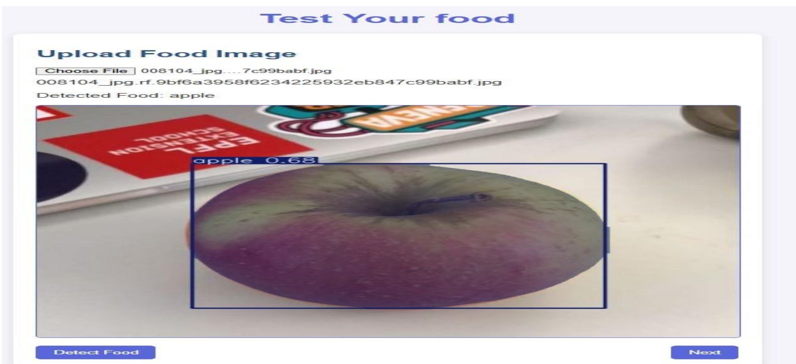


Fig 4: Detecting the Apple to calculate Nutrition Quantities

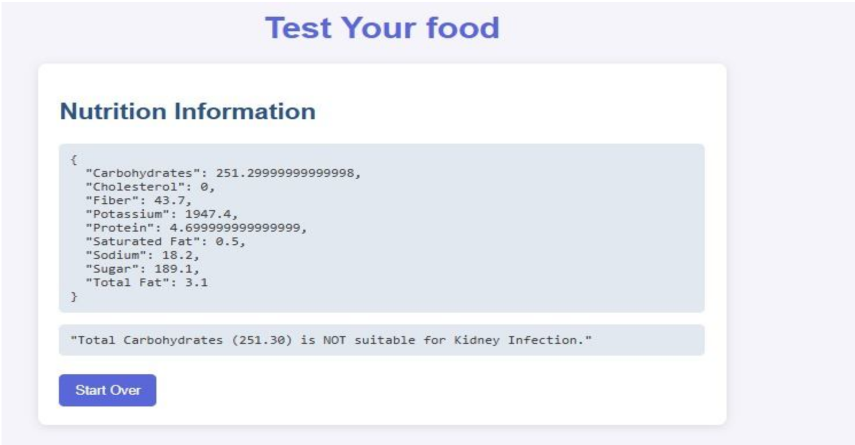


Fig 5: Nutritional Information present in Apple After Detecting

VI. Conclusion & Future Work

This project leverages deep learning, specifically the YOLO (You Only Look Once) algorithm, to achieve accurate, real-time nutrition estimation and nutrient composition analysis of various food items. By employing YOLO for image-based food identification, the system efficiently recognizes food items and determines their nutritional profile. Combined with tailored analysis, the system evaluates each food item's suitability based on the user's specific health conditions or dietary restrictions. This approach not only facilitates personalized dietary recommendations but also empowers users to make health-aligned choices quickly and easily. In future iterations, this project could be expanded to offer complete meal recommendations by combining compatible food items into nutritionally balanced meals that align with the user's health requirements. By integrating advanced dietary frameworks and larger datasets, the system could evaluate the collective nutritional value of various food items, ensuring a balanced intake of macronutrients and micronutrients in suggested meals.

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